A Decision Support Tool for Rural Water Supply Planning

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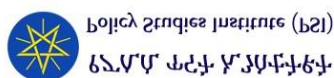
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Abstract

Over a dozen studies have examined how households who travel to collect water (about one-quarter of humanity) make choices about where and how much to collect. There is little evidence, however, that these studies have informed rural water supply planning in anything but a qualitative way. In this note, we describe a new web-based decision support tool that planners or community members can use to simulate scenarios such as (1) price, quality, or placement changes of existing sources, (2) the closure of an existing source, or (3) the addition of a new source. We describe the analytical structure of the model and then demonstrate its possibilities using data from a recent study in rural Meru County, Kenya. We discuss some limits of the current model, and encourage readers and practitioners to explore it and suggest ways in which it could be improved or used most effectively.

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Keywords: rural water supply; decision support; development economics; water supply engineering

JEL Codes: Q25, O13

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1. Introduction

Approximately one-quarter of households in the world do not have access to improved drinking water services on premises. The issue is concentrated in rural areas: 40% of rural households overall, and 75% of rural Sub-Saharan African households, travel to collect water (JMP 2019). Continuing four decades of large-scale investments in rural water supply, governments and non-profits continue to invest heavily in improving this situation by giving households access to more and higher quality water sources like protected springs and drilled boreholes. "Demand-led" approaches of the 1990's recommended that communities be given a voice in choosing the right type of technology and be provided with a sense of ownership over the built facilities. Evidence suggests these policies have improved the sustained functionality of water points (Whittington et al. 2009), but problems remain. Approximately one in three handpumps is estimated to be out of service at any one time (Rural Water Supply Network 2013) and user fees and cash on hand continue to be problems (Koehler, Thomson and Hope 2015).

These rural households often face a complicated decision in procuring water supply. They may have access to several sources which vary in quality (e.g. protected deep boreholes vs. polluted surface sources), distance from home, hours of availability, and financial price (either per trip or per month). An urban household with a piped connection must choose how much water to consume from the tap and whether to treat that water, but a rural household makes a three-part decision: where to collect, how much water to collect, and whether the water should be treated.

A large number of empirical studies have examined these types of choices, though the vast majority are in urban or small-town settings where the relevant decision is whether to supplement the unreliable piped supply with non-network water.[1] Relatively few have examined choices in rural settings (White, Bradley and White 1972; Briscoe, Chakraborty and Ahmed 1981; Mu, Whittington and Briscoe 1990; Kremer et al. 2011; Gross and Elshiewy 2019; Wagner, Cook and Kimuyu 2020), and only two (Gross and Elshiewy 2019 and Wagner et al. 2020) have examined rural households' decisions of *how much* water to collect, what economists call "water demand". A large number of studies have used stated preference methods (i.e. contingent valuation) to estimate households' willingness-to-pay for improvements in access or quality (see van Houtven et al. (2017) for a recent review). Although these studies can be used

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[1] See Briscoe, Chakraborty and Ahmed 1981; Mu, Whittington and Briscoe 1990; Persson 2002; Larson, Minten and Razafindralambo 2006; Nauges and Strand 2007; Basani, Isham and Reilly 2008; Cheesman, Bennett and Son 2008; Nauges and Van Den Berg 2009; Boone, Glick and Sahn 2011; Kremer et al. 2011; Onjala, Ndiritu and Stage 2014; Uwera and Stage 2015; Gross and Elshiewy 2019.

to estimate the percentage of people who will use a source at a given price, they are generally silent on quantity responses.

Despite this body of research, however, it appears that the results have not affected water supply planning on the ground in anything but a qualitative way. Water supply planners or community members evaluating options are routinely faced with difficult questions that this research could inform. Should we increase the per-container fee to improve cost recovery? If we do, what fraction of customers will revert back to using surface sources? How much less water will an average household collect? Where should we locate new water points? How many new water points should we install? What will happen to household water use if one of the water points fails? If we convert an open spring to a protected source and improve quality, what fraction of the population will use it?

These studies could be used to make predictions for questions like these, but we are unaware of a prediction tool or decision-support system freely and currently available for rural water planners or communities to use. Hopkins et al. (2004) use the results of a contingent valuation study in Rwanda to parameterize two location models (the p-median and location set-covering model[2]) to optimize how many new water points to build and where to place them given a cost-recovery constraint or a minimum service level (maximum distance) constraint. Hopkins (2015) builds on this work, applying the optimization model to rural Mozambique and adding a model component to estimate (and optimize) the net social benefits to users by valuing time savings. In both cases, the model emphasizes mathematical optimization given constraints, though the authors make clear that the model could and should be used as an input into a complex, community-driven planning process.

At the same time, the advent of water point mapping (AkvoFlow, mWater, Water Point Data Exchange (WPDx)) has dramatically increased the amount of geospatial water point data available to planners. WaterAid's Water Point Mapper tool[3] is a good example of how water point data is currently being used to produce maps that can be used for monitoring and planning based on minimum-service criteria. The tool does not allow users to interactively explore how changing parameter assumptions or modeling various scenarios would change various outcomes of interest.

In this note, we describe a decision support tool for rural water supply that planners or community members can use to simulate scenarios such as (1) price, quality, or placement

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[2] Note also that ESRI's ArcGIS software includes a "location-allocation tool" that uses similar approaches to choose optimal locations of facilities, which include water points. As Hopkins (2015) points out, however, the tool cannot be used to optimize the number of water points, and of course the software is proprietary.

[3] www.waterpointmapper.org

changes of existing sources, (2) the closure of an existing source, or (3) the addition of a new source. The tool is freely available on the web[4], and draws from empirical research on household water source choice and demand studies. We plan to continue refining the tool, and welcome input from possible users for the types of questions and interfaces they would find valuable. The objective of this practical note is to describe the basic analytical structure of the model and show how the model might be used, in a case study from rural Meru County, Kenya. We close with a discussion of the analytical limits of the current version of the model and a call for more empirical research on rural water demand to inform future versions of the model.

2. Methodology

2.1 Framework

Our model assumes that the decisions of 1) how much water to collect and 2) which sources to collect from happen sequentially but in an inter-related way. Households first make the decision of how much to collect, and then decide how to allocate that "demand" across sources available to them. This approach is called the "linked demand" model, and originated in the literature studying how people make decisions about visiting recreation sites for fishing, boating, hunting, etc. (Bockstael, Hanemann and Kling 1987). Other studies have modeled these inter-related decisions by first predicting which source will be chosen, and then predicting demand/quantity conditional on the household choosing that source (Gross and Elshiewy 2019; Nauges and Strand 2007). We prefer the linked demand approach because it, similar to the "almost ideal demand system" approach (Coulibaly, Jakus and Keith 2014; Deaton and Muellbauer 1980), allows households to use more than one source at a time (Elliott et al. 2017).

As a simple example, the model first predicts how much water (in 20 liter jerricans) that a household will collect in total over a week, which we will discuss in more detail shortly. Suppose this total weekly demand is 50 jerricans (1,000 liters). We then predict how the household will allocate those 50 jerricans across the sources available to them by predicting the probability that a household will use a particular source, again described further below. Suppose our example household had four publicly-constructed boreholes and a river within 3 kilometers walk. Suppose that each of the four boreholes charged a user fee. Based on the distance between the household and each source, the source's price, and the source's quality, we predict the probability that the household will collect from that source. Our model might predict the household has an 80% probability of choosing a borehole which is closest to them and happens to also be the cheapest, a 10% probability of collecting from a second borehole which is

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[4] The model can be accessed at www.ruralwaterdecisions.org

somewhat farther away but has higher quality, and a 10% probability of collecting from the free, poor quality river. Suppose the other two boreholes are so distant from the household that our model predicts zero probability of the household using them.[5] Demand at each source is calculated by multiplying total demand (50 jerricans) by the probability of use. We would predict the household would collect 40 jerricans from the first, closest borehole (50 * 0.80), 5 jerricans from the other borehole and 5 jerricans from the river (50 * 0.10). By aggregating household demand at each source, we can calculate statistics at the source level: how much water will be collected (and revenue raised) from the first borehole by *all* households in the vicinity.

2.2 Parameters and Model Calculations

The probability of a household collecting from each source is derived from several empirical studies that rely on "random utility" theory in economics (McFadden 1974) to explain a household's choice of water source. These studies have generally found that price, distance to source, quality and reliability are all important determinants (Briscoe et al. 1981; Mu et al. 1990; Persson 2002; Larson, Minten and Razafindralambo 2006; Nauges and Strand 2007; Basani, Isham and Reilly 2008; Cheesman, Bennett and Son 2008; Nauges and Van Den Berg 2009; Boone, Glick and Sahn 2011; Kremer et al. 2011; Onjala, Ndiritu and Stage 2014; Uwera and Stage 2015; Gross and Elshiewy 2019). Our model focuses on how three key source attributes affect the probability of choosing a source: distance, price, and quality.[6] The first two attributes are continuous measures, but quality is assumed to be discrete: either "poor", "fair", or "good". Households' preferences for each attribute are represented by three parameters – one for each attribute (distance, price, and quality). The first two parameters are negative (households prefer shorter distances and lower prices in choosing a source) and the third is positive. The magnitude of each parameter indicates how sensitive households are to that attribute: if the price parameter increases in magnitude, it indicates that households are more sensitive to price. We leave the interpretation of these quality categories to model users, but in general we would map these categories to the WHO/UNICEF's Joint Monitoring Program as follows: "poor" quality would include surface and "unimproved" sources (i.e. unprotected wells or springs); "good" quality

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[5] In practice, we limit households to only collecting from their top three sources (ranked by the indirect utility function). This is a crude way to prevent our model from (unrealistically) predicting positive collection by each household from each source in the study site.

[6] More specifically, the model assumes each household's primary source is the one that provides the most utility, where the "indirect" utility function for water source j to household i is given by: V_{ij} = -0.11*Price – 0.52*Distance+ 0.1*(Good Quality) – 0.1*(Poor Quality). Then the probability of household i collecting from source j, where all other sources in the household's choice set are denoted k, is given by: $\text{Pr}_{ij} = \frac{e^{V_{ij}}}{\sum_k e^{V_{ik}}}$.

would include "safely managed" sources and possibly "basic" sources; and "fair" quality would include "limited" and possibly "basic" sources. Although some studies have included the source's availability or potential for interpersonal conflict as attributes, we omit them here for parsimony, to focus on the three most important attributes. We also omit wait times, which we discuss below.

We use base case parameters that are taken from a combination of Wagner et al. (2020) and our judgment about the existing literature. The user can, however, adjust the parameters of the utility function. For example, if she believes households are more sensitive to price increases than our base case assumption, she can change the value from the default price parameter of -0.11 to a higher absolute value, i.e. -0.3. We implement this in the tool with an input field, where the range is bounded by the high and low estimates from the empirical literature (Table 1).[7]

Table 1. Base Case Parameters Used

Parameter	Base Case Value [Range]
Source choice (Prob. of choosing source)	
Price (per 20L jerrican)	-0.11 [-1, 0]
Distance (meters)	-0.52 [-2, 0]
Good quality	0.10 [0,1]
Poor quality	-0.10 [-1, 0]
Household demand (20L jerricans per week)	
Household size	7.28
Choice set quality	12.52

There are only two existing studies examining total household water demand, or volume, among rural, unconnected households (Gross and Elshiewy 2019; Wagner et al. 2020). We follow the latter in modeling household demand as a function of only two parameters: household size and "choice set quality". The choice set quality is a parameter linking the source choice and water demand decisions; it is unique for each household, and is the sum of the utility obtained

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[7] Implicitly, we only model collection from public sources (i.e. we do not model the household's decision between using their private source and collecting from a public source). We do, however, adjust demand calculations to reflect the prevalence of private sources in the study site.

from collecting from each available source weighted by the probability that the household collects from that source (Hanemann 1982, Creel 1992). Intuitively, a household with more high-quality, low-cost sources close to them will have a higher "choice set quality" and thus collect more water per capita than a household with only one poor-quality source.[8] We again allow the user to vary this parameter; the bounds are given by the 95% confidence interval found in Wagner et al. (2020), currently the only study to use this approach. The model assumes an average household size for the entire study site since data on individual household sizes would typically be unavailable to a planner. We use a default household size of 5 members based loosely on rural Kenya. We assume that increasing household size by one member increases water demand by 7.28 20L jerricans per week, with a household-level intercept of 0.77 jerricans per week (average choice set quality is 2.16). This corresponds to approximately 37 liters per capita per day for a family of 5.[9]

3. Case Study

We demonstrate the decision-support tool by analyzing a sample dataset from Meru County, Kenya. This data comes from the most recent water source choice and demand study (Wagner et al. 2020), and is available for download at www.ruralwaterdecisions.org. In what follows, we describe the results of three simulations analyzed using the decision-support tool.

Before discussing the simulations, we present results from a benchmark scenario. Figure 1 displays the set of available sources in our study site, along with color-coded market segments. Households residing inside the bounds of each market segment are predicted to primarily use the water source of the corresponding color. For example, households located in the light blue-shaded region on the right of the map are predicted to primarily collect water from source 4. Figure 2 shows only the northeast region of our study site, which will be the focus of the following simulations.

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[8] Choice set quality is implicitly a function of the attributes of available sources and household preferences over those attributes via the utility function. Formally, the household demand equation is given by: total weekly demand (20L containers)= 0.77+ 12.52*(choice set quality)+7.28*(household size).

[9] We omit for now variables on income or wealth from the household demand equation. These variables are typically included in models of demand for piped water and were included in the two rural water demand studies cited above. These analyses are typically identified based on variation in income or wealth across households in the *same* study site, but again we expect most users would not have detailed household income information. We do not believe there is currently enough information in the existing literature to know how water demand varies *across* study sites that vary in average income or wealth levels. The model can easily be adapted should this information become available.

Figure 1: Benchmark Scenario (full study site)
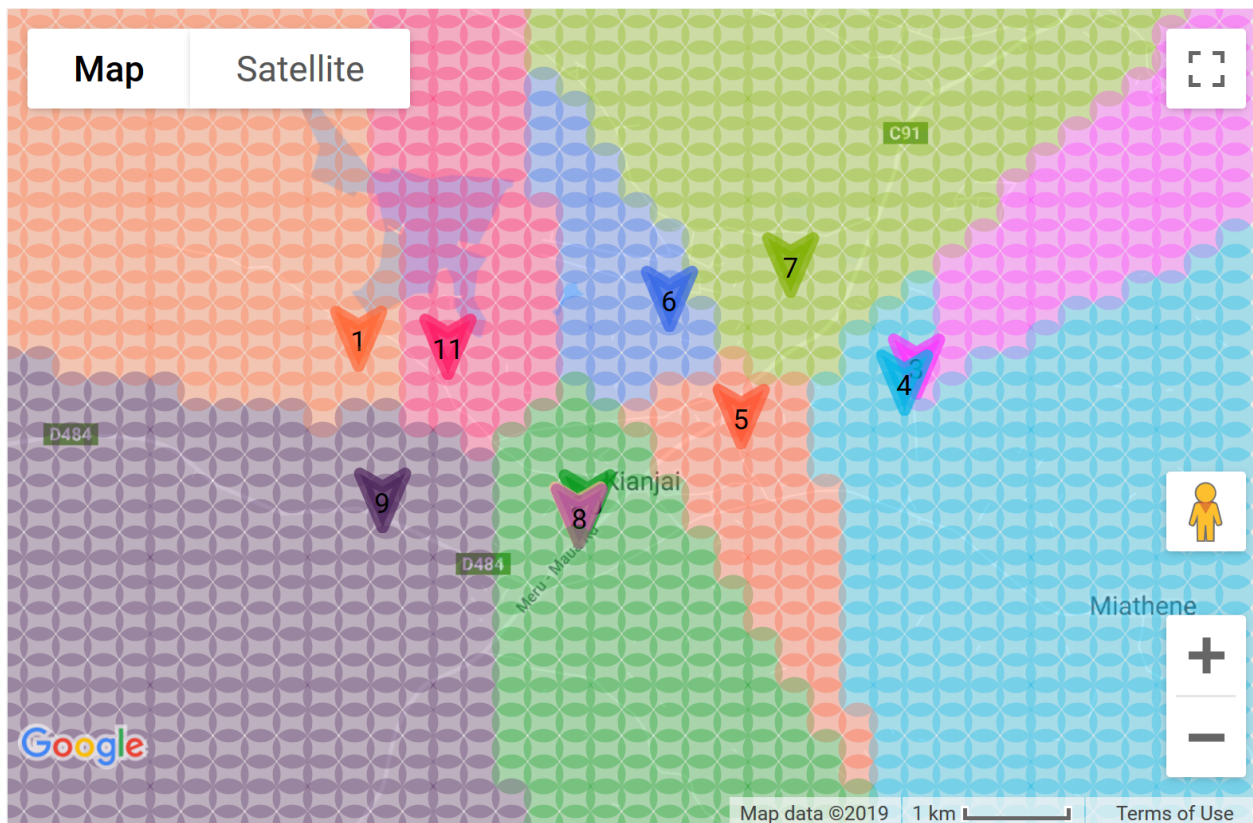
The simulations are used to test how changes in source attributes affect both source- and community-level water demand statistics. There are four sources located within the subregion of interest. Each of these sources has benchmark attributes (Table 2). In each of the three simulations, we alter the source attributes of one of the sources located in the subregion. Simulation 1 increases the quality at Source 3. Simulation 2 increases the price at Source 7. In Simulation 3, we assume Source 5 has fallen into disrepair and has been closed.

For each simulation, we generated maps that depict color-coded market segments (Figures 3-6). We also generated a set of demand statistics for the benchmark scenario and each of the simulations (Table 3). For brevity, we will compare the results of each simulation to those of the benchmark case, but cross-simulation comparisons are also insightful.

Table 2: Source Attributes – Baseline Scenario and Three Simulations

|	Attributes	Benchmark	Simulation 1	Simulation 2	Simulation 3
Source 3	Price	1 Ksh	1 Ksh	1 Ksh	1 Ksh
	Quality	Poor ⟶	**Good**	Poor	Poor
Source 4	Price	2 Ksh	2 Ksh	2 Ksh	2 Ksh
	Quality	Fair	Fair	Fair	Fair
Source 5	Price	2.5 Ksh	2.5 Ksh	2.5 Ksh	**n/a, closed**
	Quality	Good	Good	Good	**n/a, closed**
Source 7	Price	2 Ksh	2 Ksh ⟶	**5 Ksh**	2 Ksh
	Quality	Good	Good	Good	Good

Simulation 1 tests the effects of a change in source quality on households' choice of primary source and on demand. Notice that, when the quality of Source 3 increases from 'poor' to 'good', households that were previously using Source 4 ('fair' quality) switch to using Source 3 (Table 3). While households have stopped using Source 4 as their primary source, they still collect from Source 4, though less frequently. The new market share captured by Source 3 due to improved quality increases demand from 6,822 to 9,215 jerricans at Source 3.

In Simulation 2 we investigate the effect of increasing the price at Source 7 from 2 to 5 Ksh. We see that many households that were previously collecting primarily from Source 5 have shifted their primary collection to Sources 4, 5, and 6. Due to the price increase, water collected at Source 7 drops dramatically, from 6,278 to 4,264 jerricans, but revenues increase because the fall in demand is offset by the increased price.
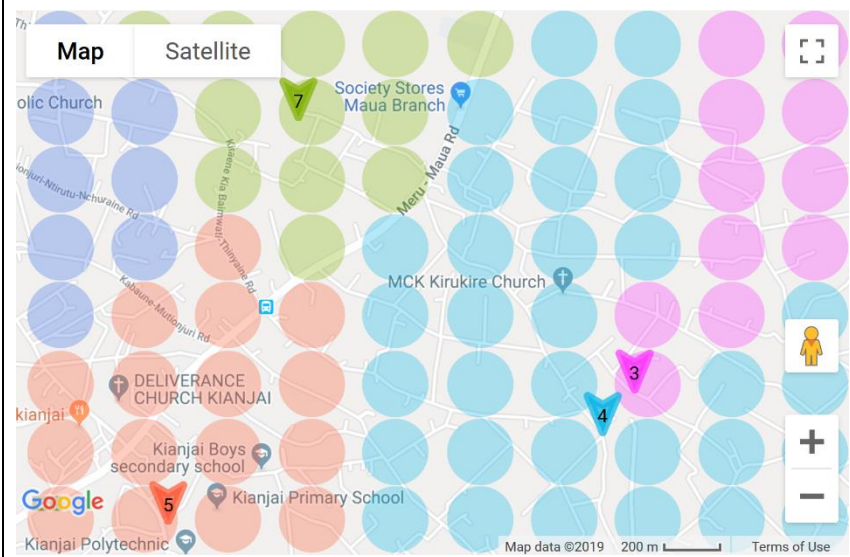
Figure 2. Benchmark Scenario (Subregion)
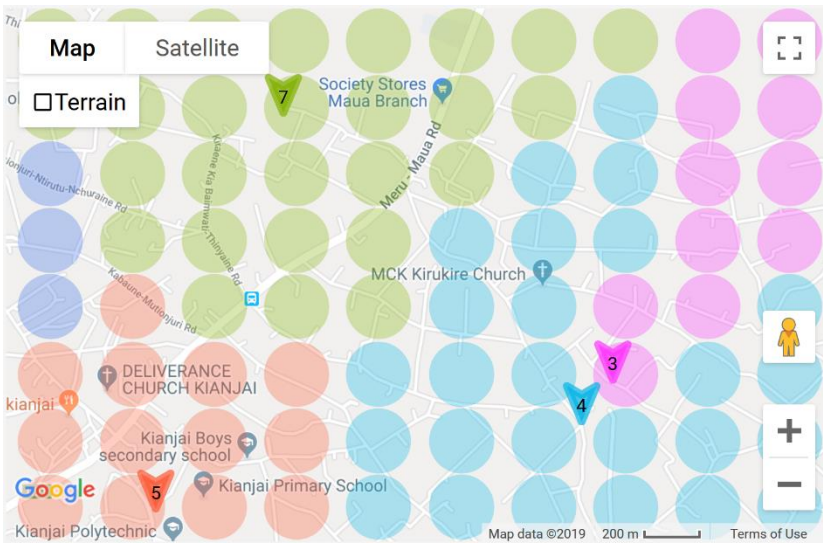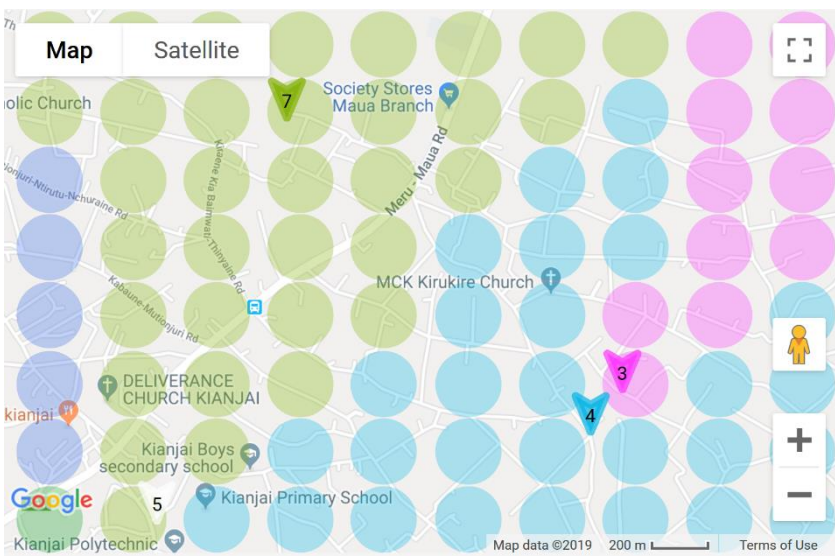

Figure 3. Simulation 1: Increase the Quality of Source 3 from 'Poor' to 'Good'
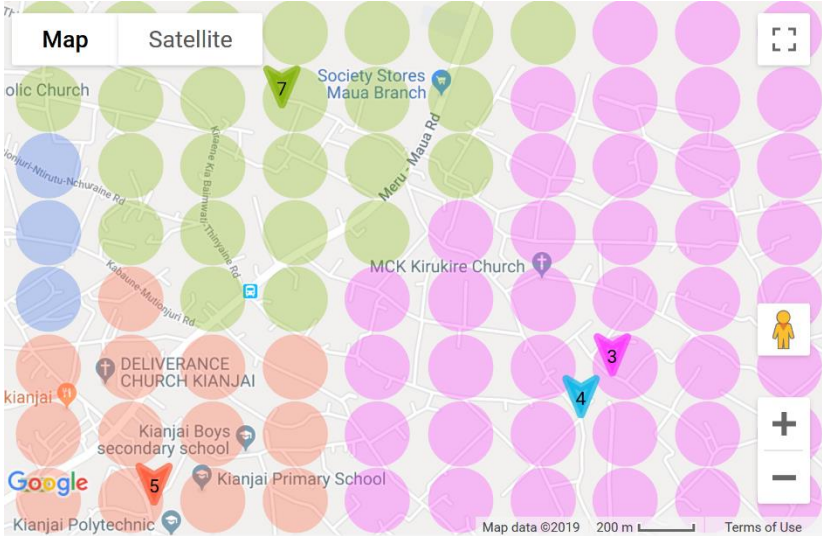
Figure 4. Simulation 2: Increase the Price of Source 7 from 2Ksh to 5Ksh

Figure 5. Simulation 3: Source 5 (in white) Breaks Down

Finally, in Simulation 3, we consider how the closure of Source 5 affects source choice and demand. We see that when Source 5 closes, Sources 4 and 7 capture most of the household demand. Households, however, must now travel much farther to collect water, resulting in the lowest total demand across the three simulations.

Table 3: Monthly Demand Statistics (during the dry season) – Baseline and Three Simulations

		Benchmark	Sim. 1 (quality change #3)	Sim. 2 (price increase #7)	Sim. 3 (#5 closes)
Study-site	Percent of households using 'good' quality sources	0.20	0.47	0.17	0.18
	Average weekly water demand (20L jerricans)	59.5	59.5	58.9	58.0
	Average liters per capita per day (liters)	34.0	34.0	33.6	33.2
Source 3	Number of primary users (households)	68	344	102	70
	Total demand (20L jerricans)	6,822	9,215	7,307	7,233
	Total revenue (Ksh)	6,822	9,215	7,307	7,233
Source 4	Number of primary users (households)	242	0	259	261
	Total demand (20L jerricans)	8,191	7,363	8,760	8,946
	Total revenue (Ksh)	16,382	14,726	17,519	17,891
Source 5	Number of primary users (households)	49	48	52	n/a
	Total demand (20L jerricans)	4,634	4,272	5,465	n/a
	Total revenue (Ksh)	11,584	10,680	13,664	n/a
Source 7	Number of primary users (households)	145	134	73	170
	Total demand (20L jerricans)	6,278	6,395	4,264	7,787
	Total revenue (Ksh)	12,557	12,791	21,321	15,574

4. Discussion

We begin by acknowledging some of the limitations of the current version of the model which we hope to address in the future. First, households spend time not only in traveling to collect water but also by waiting in queues at the source. The model does not incorporate waiting times, which is equivalent to a strong assumption that waiting times are zero at all

sources or are equal at all sources (and thus affect the probability the same). Further versions of the model could include the ability for the user to input fixed wait times that vary by source. A more complex dynamic model could allow wait times to increase at a given source as more users are predicted to use that source, feeding back into the decision to use it.

Second, having water delivered to the household by a private vendor is a common feature in many communities, including our study site in Kenya, but is omitted from the model. Similarly, the model currently allows the user to enter the fraction of households with a private, piped connection and then assumes that these households collect water exclusively from their piped connection and do not contribute to demand from sources away from home. Future versions could allow a user to add vending as a water supply option in a community at a fixed price per jerrican and quality. The model would then add vending as a spatially-indeterminate "source" with zero distance. Similarly, we could allow households with piped connections to supplement with sources away from home.

In many places, including some parts of our study site, the groundwater table is shallow enough for households to invest capital costs in digging or drilling wells on their property. This reduces their water collection times and volumetric water prices to zero, and quality can vary depending on the groundwater and the actions households take to treat the well water. Incorporating this investment decision would require adding a time dimension to the model beyond the simple monthly time step in the current version. Households would compare the capital costs of investing in the well against the expected benefits over its useful life (years, if not decades), which are in turn a function of the quality of water sources away from home both currently *and* predicted into the future.

Our model is silent on water availability. It is possible that our demand calculations could not be met by available supply, or that aggregate demand over time could lower water tables and dry up some groundwater wells. We are not hydrologists, but would welcome a collaboration to link our demand model with a groundwater model or surface water models (i.e. SWAT, VIC) that could incorporate changes in precipitation (from downscaled climate models) or changes in landscape, soil conservation practices and/or forest cover.

Finally, our parameterization of water quality is admittedly simplistic: water can be either "good", "fair" or "poor". Water quality is a multi-dimensional attribute that includes taste, color/turbidity, and salinity, all of which are perceptible to users. It also includes microbial contamination, which is not readily apparent to users but may be reflected in users' perceptions of the health risks of using that source based on past experience. Microbial contamination can be

measured objectively, but it is users' perceptions of those risks that drive decisions of source choice and demand.

Although researchers have conducted a large number of randomized trials measuring willingness-to-pay for point-of-use water treatment devices like filters or chlorine tablets (e.g. Ashraf et al. (2010)), there are many fewer estimates of how *perceived* water quality (Jeuland et al. 2015; Somanathan 2010) impacts source choice decisions. This would improve the accuracy of our model. In general, we hope this note illustrates the point that more sophisticated demand-side water supply planning tools could be helpful to the sector, but are at the moment informed by only a handful of studies. More research in this area would be helpful.

We would encourage practitioners who are interested in learning more about the tool to visit ruralwaterdecisions.org to explore how it works, and to contact us with feedback and recommendations for future model iterations. One can imagine practitioners and researchers forming a constructive feedback loop using the model as a core. As a first step, an implementer can use the model in a given location with information only on water source locations and attributes to predict household behavior. This ex-ante prediction could then be compared to water point consumption data (if metered). If the model performs poorly, additional data collection from intercept surveys at water points or short household interviews could provide data for researchers to generate site-specific preference parameter estimates that improve model fit for future use at that location. When such studies are well-done and made publicly available (ideally in peer-reviewed outlets), they could be added as parameter value choices in the decision-support tool. This would also add to the public good of improving our ability to accurately forecast rural water choices and speed progress towards achieving the Sustainable Development Goals and maintaining the gains achieved.

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